Surgical Phase Detection Using Deep Learning
Proposal & Plan

Xiaorui Zhang, Wenkai Luo, Xucheng Ma

February 2022

1 Stated topic and goal

Surgical phase recognition plays a crucial role in the era of digitized surgery. Deep learning solutions have seen great success in endoscopic surgeries. Currently, no prior work has investigated its application in skull-base surgery (Cortical Mastoidectomy). This project will benchmark existing DL solutions and create an innovative DL segmentation algorithm in skull-based surgery.

2 Team members, mentor

- **Students**:
  Xucheng Ma, Xiaorui Zhang, Wenkai Luo

- **Mentors**:
  Max Li, Danielle Trakimas, Dr.Francis Creighton, Prof. Mathias Unberath, Prof. Russ Taylor

3 Relevance/importance

Surgical phase recognition has numerous potential medical applications. Such as automatic indexing of surgical video databases and real-time operating room scheduling optimization. It's also a foundation of an intelligent context-aware system, which facilitates surgery monitoring, surgical protocol extraction, and decision support. To be more specific on our project, Mastoidectomy is a highly delicate and complex surgery. There are many facial nerves and blood vessels around the region of operation. It would be ideal for the surgeon to have an intelligent context-awareness system to facilitate decision-making. Our online video segmentation model would be necessary for this system to be aware of the current surgical phase.

4 Short technical summary of approach

Since considering the surgical phase segmentation as a sequential problem rather than a per-frame classification, the proposed deep learning neural network needs to extract spatiotemporal features.

- *Spatial feature extraction:*
  One of the essential parts of the architecture is the spatial feature extractor, which extracts the feature from the frames and converts them into an abstract representation format. Based on the idea of transfer learning, the pre-trained convolutional neural network(CNN) models

have been proved to be stat-of-the-art on many computer vision tasks. Furthermore, the pre-trained model can extract more specific features with the fine-tuning process using the mastoidectomy dataset.

- *Spatiotemporal model:*
  The most crucial part of the architecture is the spatiotemporal model, which is to capture the temporal patterns from the extracted per-frame spatial features from video. The temporal patterns are essential to make a correct prediction since the patterns can provide clues of surgery environment change and the instrument motion. Recurrent neural networks such as LSTM, temporal convolution neural network (TCN), and transformer are promising architectures for capturing the temporal pattern. However, some research argues that LSTM can only capture short-term information while long-term context might be beneficial for accurate segmentation. All of them will be implemented on the mastoidectomy dataset in our project.

- *High-level Classifier:*
  The fully connected neural network(FCNN) will then be trained with the ground truths to make the phase decision based on the extracted spatiotemporal feature since it can approximate any arbitrary function. One crucial concern is the over-fitting issue, which can be compensated by different training skills such as drop-out and batch-normalization.

5 Deliverables

Project deliverables are listed as follows:

- **Minimum Deliverables**
  - New dataset from cortical mastoidectomy videos (with Danielle's help)
  - At least three methods
  - All methods trained and evaluated on the new dataset

- **Expected Deliverables**
  - Experiments and comparison with existing methods
  - Ablation study

- **Maximum Deliverables**
  - Conference paper

6 Timeline & Milestones

Figure 1 shows the project timeline. Milestones are labeled in blue, and deadlines for resolving dependencies are labeled in red. Other entries in the timeline indicate either start point or end point of tasks.

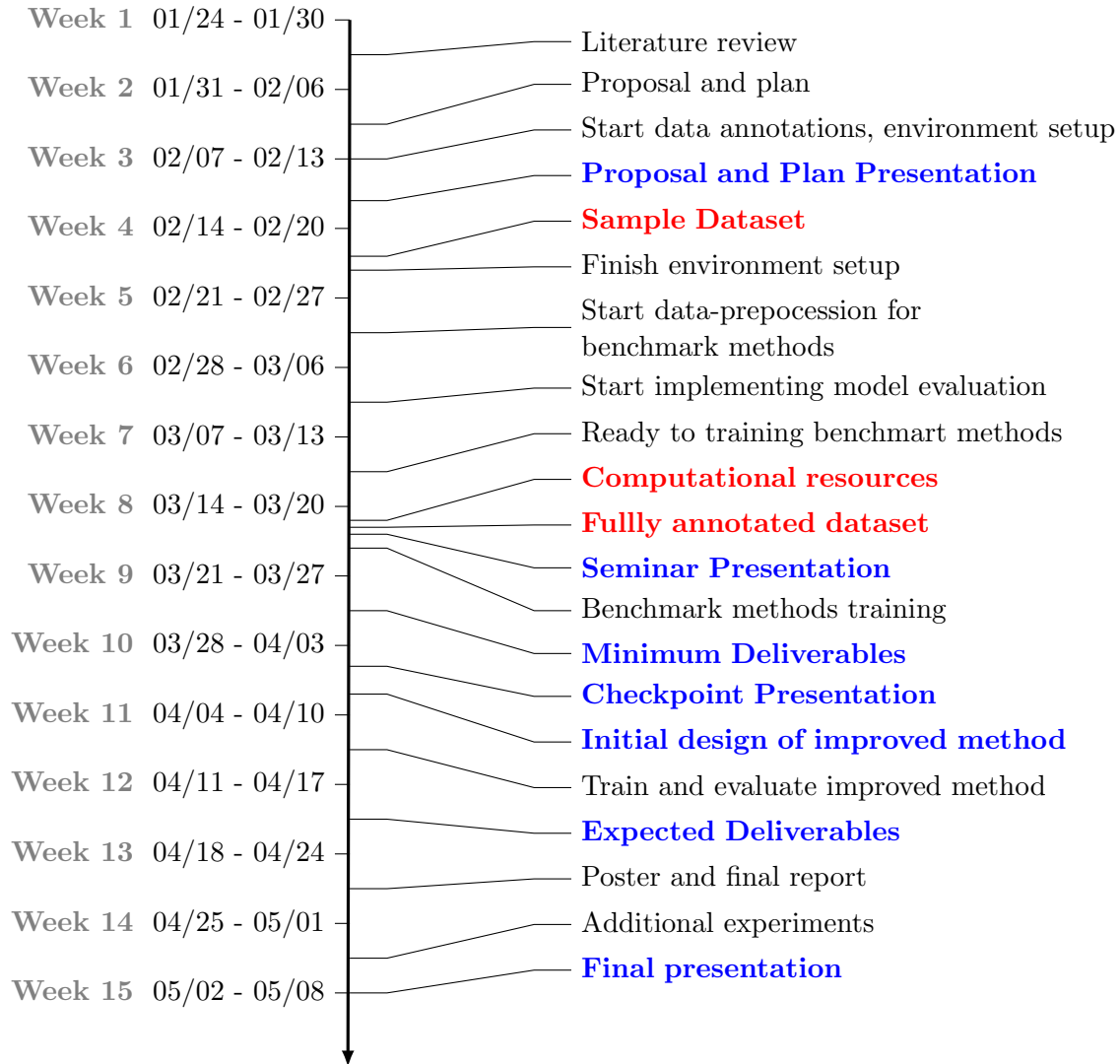Figure 1: Project timeline, Milestones labeled in blue, Deliverables deadline labeled in red

7 List of dependencies & plan for resolving

Dependencies

Main Dependencies	Sub Dependencies	Contact	Expected Date	Status	Alternative solution
Dataset	Data Generation	Dr. Danielle Trakimas	/	Ongoing	N/A
	Annotation Protocol	Dr. Danielle Trakimas	02/18	Complete	N/A
	Data Annotation	Dr. Danielle Trakimas	03/17	Ongoing	N/A
	IRB Training	Dr. Danielle Trakimas	02/11	Complete	N/A
	IRB Amendment	Dr. Danielle Trakimas	02/25	Ongoing	Use the safe desktop to do the preprocessing of the video, and onedrive streaming will be the alternative solution to address the failure of the IRB amendment
Computational Resources	GPU	Max Li	02/18	Complete	Use the online GPU resource such as Amazon cloud or Colab(Need to get the budget from mentors)
	Server Remote Access	Anton Deguet	02/18	Complete	Set up the computer in a physically available environment, and we need to use that computer to finish the project
Existing Framework & Public Dataset	Framework	Max Li	02/11	Complete	Implement and reproduce the frameworks based on the paper by ourselves using PyTorch
	Laparoscopic Public Dataset (Cholec80)	Max Li	02/11	Complete	Find Another available public dataset
Clinical Advice	Clinical Advice	Dr. Danielle Trakimas	/	Ongoing	Need to find another expert to provide clinical advice

8 Management Plan

- We meet with our mentors and report weekly progress every Friday.

- Slack are used for daily communication.

- All project relevent codes and documentation are managed with git.

- Project progress is monitored with Gantt Chart.

Reading List

[1] Andru Putra Twinanda, Sherif Shehata, Didier Mutter, Jacques Marescaux, Michel de Mathelin, and Nicolas Padoy. Endonet: A deep architecture for recognition tasks on laparoscopic videos. *CoRR*, abs/1602.03012, 2016.

[2] Xiaojie Gao, Yueming Jin, Yong-Hao Long, Qi Dou, and Pheng-Ann Heng. Trans-svnet: Accurate phase recognition from surgical videos via hybrid embedding aggregation transformer. *CoRR*, abs/2103.09712, 2021.

[3] Carly Garrow, Karl-Friedrich Kowalewski, Linhong Li, Martin Wagner, Mona Schmidt, Sandy Engelhardt, Daniel Hashimoto, Hannes Kenngott, Sebastian Bodenstedt, Stefanie Speidel, Beat Müller, and Felix Nickel. Machine learning for surgical phase recognition a systematic review. *Annals of Surgery*, Publish Ahead of Print, 11 2020.

[4] Henry Lin, Izhak Shafran, David Yuh, and Gregory Hager. Towards automatic skill evaluation: Detection and segmentation of robot-assisted surgical motions. *Computer aided surgery : official journal of the International Society for Computer Aided Surgery*, 11:220–30, 10 2006.

[5] Tobias Blum, Hubertus Feussner, and Nassir Navab. Modeling and segmentation of surgical workflow from laparoscopic video. volume 13, pages 400–7, 09 2010.

[6] Joonmyeong Choi, Sungman Cho, Jong Chung, and Namkug Kim. Video recognition of simple mastoidectomy using convolutional neural nets: Detection and segmentation of surgical tools and anatomic regions. *Computer Methods and Programs in Biomedicine*, 208:106251, 06 2021.

[7] Colin Lea, Joon Hyuck Choi, Austin Reiter, and G Hager. Surgical phase recognition: from instrumented ors to hospitals around the world.

[8] Manish Sahu, Angelika Szengel, Anirban Mukhopadhyay, and Stefan Zachow. Surgical phase recognition by learning phase transitions. *Current Directions in Biomedical Engineering*, 6(1):20200037, 2020.

[9] Colin S. Lea, Austin Reiter, René Vidal, and Gregory Hager. Segmental spatio-temporal cnns for fine-grained action segmentation and classification. *arXiv: Computer Vision and Pattern Recognition*, 2016.

[10] Yueming Jin, Yonghao Long, Cheng Chen, Zixu Zhao, Qi Dou, and Pheng-Ann Heng. Temporal memory relation network for workflow recognition from surgical video. *IEEE Transactions on Medical Imaging*, 40(7):1911–1923, 2021.